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Side effects of decision guidance in decision support systems

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Abstract

Ideal Decision Support Systems (DSS) provide aid in the attainment of a solution to a particular problem of the user. However, during system interaction, the dialogue design of the DSS has the potential to influence the outcome of the solution. This side effect may or may not be desirable, but system designers must be aware of the potential impact. A laboratory study described in this report examines the significance of the impact. A total of 46 subjects conducted decisions on forecasting methods under two different design structures for DSS interfaces. An increase in guidance provided by the system led to a significant change in the decision model selected. This change in model selected resulted in a number of different solutions to the study's forecasting problem. In application settings, such impacts need to be evaluated prior to implementation to avoid the situations where the software influences the decision process.

Keywords: Decision support systems; Decision guidance; User interface design

1. Introduction

Interest in the use of computer-supported decision making has grown in recent years. Such systems are termed Decision Support Systems (DSSs). They facilitate decision making by empowering users with essential data and appropriate quantitative models. In the course of interacting with a DSS, users may have numerous opportunities for exercising judgments. Some judgments pertain to task ordering, others require input of predictions or evaluations otherwise unavailable to the system. Some judgements concern

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what to do next: Should I run a moving-average or a regression forecasting method on the data? Should I run the same data analysis again with different parameters? Other judgements are predictive: What will the interest rate be in the second quarter of this year? How many units of my product will I sell this year?

An interactive DSS must provide a means for users to communicate these judgmental inputs. Menus, fill-in tables, and on-line help-screens are used widely for this purpose. When interacting with a DSS, a key issue is whether the dialogue mechanisms affect the substance of users' judgmental inputs. As examples, menus may lead to order effects as users may tend to select the first or last items on menus [1]. Use of graphics as opposed to data sets impact judgment [2]. For instance, numerical data are commonly organized into tabular arrangements, while there are a variety of standard graphical arrangements of pictorial elements (e.g. bar charts, scatter plots, and so on). Some researchers have found that graphical presentations are more useful when evaluating information in order to determine promising directions in the search for an optimal solution but when the task requires the determination of exact data values for computational purposes, graphical reports are less useful than tabular ones [3]. On the other extreme, a DSS may embed a knowledge-based system that recommends actions and responses to its users. The purpose is to guide the user toward a solution in a rigid algorithmic fashion. Either deliberately or inadvertently a DSS may guide its users in performing the required judgments [4,5].

Recent DSS studies focused on important characteristics and design issues [6,7]. This stream of research found that when a DSSs assistance matches the users' mental models, the more easily and quickly users learn the system. We should not limit ourselves to the study of problems concerning only existing technologies (e.g. mouse, voice, windows, and graphics). We should explore new, creative uses of advanced technologies to know what, when, and how to apply them effectively. We need to broaden research concerning how people organize, store, and retrieve concepts [8]. We also need to investigate psychological attribute (such as attitude and preference), work-related factors (such as fatigue and organizational culture), and certain physical limitations (such as hearing and vision impairment). But this cannot be easily achieved because existing technological restrictions limit the choice of dialog style and impose rigid syntax rules and recovery procedures. Further, the work is hindered by our limited understanding of users' cognitive models.

To mitigate these problems, [9] argued that a DSS should provide multi-level assistance to help users learn and use the system. For example, query-in-depth is a technique designed to provide multi-level assistance to help users at various levels of expertise learn the system [10]. Its low-level help could include brief 'how-to-do-it' and 'what-it-is-for' information that instructs users' immediate actions. If not satisfied, the user can request more advanced 'how-it-works' information for trouble-shooting. The design questions include what information should be given and when for different tasks, what ideas should be left to users inference, and how to use feedback to make learning enjoyable. When novice users make errors and are uncertain about what to do next, they often look for instructions from the system [11]. Specific 'how-to-do-it' information can be included to assist novice users in the quick completion of tasks [12]. This complex interaction usually leads to the requirement of prototypes to test and refine the interaction model. However, such complex designs and elongated development is expensive and time-consuming.

The complications and costs described above are why most of implemented DSSs lack

Method	Quickness	Expense	Frequency	Consistency	Simplicity	Detail
Moving Average	10	10	6	6	9	7
Exponential Smoothing	8	9	6	7	10	7
Times Series	6	7	8	8	8	9
Box-Jenkins	6	6	10	9	6	10

Quickness: Can the forecasting model be developed immediately? From 1 (extremely slow) to 10 (extremely quick)
Expense: Can the model be developed inexpensively? From 1 (extremely expensive) to 10 (extremely inexpensive)
Frequency: Can the model be updated easily and rapidly? From 1 (extremely difficult) to 10 (extremely easy)
Consistency: Can the model reflect environmental changes effectively? From 1 (extremely ineffective) to 10 (extremely effective)
Simplicity: Can the model be understood easily? From 1 (extremely difficult) to 10 (extremely easy).
Detail: Can the model produce a detailed forecast report? From 1 (extremely general) to 10 (extremely detailed).

Scale: 1 (Low on the attribute) to 10 (High on the attribute)

Fig. 1. Evaluation table for forecasting methods without weighting assistance.

sophisticated interactions, such as decisional guidance [13]. Decisional guidance is an interface concept to assist a user in the completion of tasks by performing functions usually left to the discretion of the user. The decisional guidance can be either predefined-informative or participative-suggestive. Predefined-informative guidance provides certain information to the user and requests additional input to complete a defined task. Participative-suggestive guidance segments the task and provides guidance steps dependent upon the action previously taken by the user.

Recent literature proposes the use of decision guidance structures where a decision support system directs its users as they structure and execute their decision-making process. Predefined-informative guidance provides pertinent information that assists the decision-maker's judgement, without suggesting how to act. Participative-suggestive guidance mechanisms facilitate users' on a more detailed level, perhaps even prompting for needed information. For example, perhaps there is a choice of forecasting techniques in a DSS. The DSS can support the decision maker's meta-choice by providing a list of these forecasting techniques and their associated properties (predefined-informative guidance). Kleindorfer [14] suggest that in differing situations, different criteria are appropriate for justifying the choice of a problem-solving technique. A table such as Fig. 1, which rates

Method	Quickness	Expense	Frequency	Consistency	Simplicity	Detail	*Weighted Score*
Weight	___	___	___	___	___	___	
Moving Average	10	10	6	6	9	7	___
Exponential Smoothing	8	9	6	7	10	7	___
Times Series	6	7	8	8	8	9	___
Box-Jenkins	6	6	10	9	6	10	___

Quickness: Can the forecasting model be developed immediately? From 1 (extremely slow) to 10 (extremely quick)
Expense: Can the model be developed inexpensively? From 1 (extremely expensive) to 10 (extremely inexpensive)
Frequency: Can the model be updated easily and rapidly? From 1 (extremely difficult) to 10 (extremely easy)
Consistency: Can the model reflect environmental changes effectively? From 1 (extremely ineffective) to 10 (extremely effective)
Simplicity: Can the model be understood easily? From 1 (extremely difficult) to 10 (extremely easy).
Detail: Can the model produce a detailed forecast report? From 1 (extremely general) to 10 (extremely detailed).

Scale: 1 (Low on the attribute) to 10 (High on the attribute)

Fig. 2. Evaluation table for forecasting methods with weighting assistance.

the forecasting-techniques with respect to selection criteria, could therefore guide decision makers by its inclusion of the criteria and visual representation of the problem. By itself, the table offers predefined-informative guidance. When assisting functions are added that empower users to manipulate the table (e.g. by allowing ranks for the criteria and computing weighted scores as in Fig. 2), the enhanced table becomes a participative-suggestive guidance mechanism [13].

Previously, interface designs, such as the popular pull-down menus and help screens, were oriented more toward the mechanics of operating system features than toward the decisional and judgmental tasks at hand. However, a number of recent researchers have begun to develop decisional guidance mechanisms [15,16]. Silver [13] touts the value of these interfaces which facilitate users deriving their own recommendations. An effective participative-suggestive decision guidance mechanism enables users to more easily manipulate the logic (rules) underlying the suggestions.

For our specific example, consider the first judgmental task often faced by a DSS user: selecting an appropriate forecasting model. A table, such as Fig. 1 above, could serve to guide decision makers. Different users would likely use different selection strategies for selecting a forecasting technique. However, when the functions in Fig. 2 are added, the enhanced table becomes a participative-suggestive guidance mechanism. A simple enhancement to the table in Fig. 1, shown in Fig. 2, adds a row to allow the assignment of weights to each criteria and a column to accumulate weighted totals for each model. In Fig. 2 the DSS designer provided basic information plus a technique (multi-attributed weighting) to assist in the selection of a model. However, the user still determines how the multi-attributed weighting technique is applied, if at all, in order to select a model.

The purpose of this study is to examine the impact of participative-suggestive guidance on a user's selection strategy and his decision making. Studying such deliberate guidance is important for three reasons. First, incorporating guidance in a DSS offers the potential of more supportive systems while raising a number of design questions. Second, understanding the consequence of deliberate guidance contributes to comprehending how DSSs may affect decision-making behavior. Third, for management, decisional guidance represents a set of new management opportunities for improving, standardizing and controlling decision performance.

2. Experimental design

To study the potential impact of deliberate guidance in a DSS on users' judgment, we examine when users interact with a model-based DSS, how participative-suggestive guidance using a multi-attributed weighting technique influences users' choice of decision strategy for selecting a forecasting model. We expect that subjects will change their selection of decision strategies when provided with participative-suggestive guidance after having made a selection with no participative-suggestive guidance.

Literature in social psychology suggests the effects of decisional guidance on strategies could be analyzed in terms of the effort with which various decision strategies can be accomplished [17,18]. Participative-suggestive guidance in a DSS provides such a cognitive incentive for decision makers. Specifically, the difference in guidance changes

the effort of each available strategy and, therefore, provides an incentive for decision makers to use different strategies.

A number of studies suggest that differences in information displays influence strategy selection through changes in either the effort or the accuracy with which various information processing activities can be accomplished. Specifically, differences in displays, task features, and decision maker knowledge change the anticipated effort and accuracy of each available strategy and, therefore, provide a cognitive incentive for decision makers to use different strategies. For instance, multi-attribute weighting decision strategy requires many extractions of numerical values. Thus, implementing an interface in a way that makes numerical value extraction easier would decrease the effort required for using this decision strategy.

Johnson and Payne [19] proposed a method for measuring the 'effort' associated with decision strategies by decomposing strategies into a sequence of component processes, called elementary information processes. These components are basic cognitive operations thought to be common to a wide variety of tasks. Examples include reading an item of information into short-term memory, adding two numerical items together, and comparing two items. A measure of effort can be calculated from the total number of component operations required to execute a particular strategy in a particular task.

In this study, some strategies for choice require more computational effort (weighted strategy) while the others require little, if any, computing. Thus, changing to an interface that makes the computations of the weighting technique easier would decrease the effort required for the more demanding technique and increase the likelihood of its use.

2.1. Subjects

The 46 subjects were part-time MBA students at two major Midwestern universities. None of the subjects had previously been subjects in any DSS experiment. At a minimum, all subjects had completed an introductory course in Management Information Systems. It has been demonstrated elsewhere that student subjects can serve as surrogates for managers in experiments on decision making [20,21].

We desired novice users since decisional guidance in a DSS is to facilitate novice users, not technical experts [13,22]. In addition, subjects with high level of forecasting knowledge might favor a certain model and therefore bias the results [23]. Therefore we prequalified the subjects by asking them six questions about forecasting models (Appendix C) to measure their knowledge in the field. None of the subjects answered more than 50% of the six questions correctly. Also, a self-report on subject's knowledge of forecasting models was asked as a check. Only three subjects self-reported somewhat good knowledge, but all three of them correctly answered only two out of six questions on the subject. Therefore, all of the subjects were considered as novice users included in the study.

2.2. Design and procedure

Two experimental sessions were conducted in this study. The first experimental session was a within-subject design in which 30 subjects were presented each different guidance of the same problem. One advantage of the within-subject design is statistical power, which can help to compensate for the limited number of subjects in a study [24]. One

Table 1
Number of subjects using each decision strategy

	Multi-attribute weighting	Elimination by aspects	Satisficing	Comparing by Pair	Others	Total
Experimental session 1: Predefined-informative guidance	8	4	6	5	7	30
Experimental session 2: Predefined-informative guidance	2	3	1	1	1	8
Experimental session 1: Partitipative-suggestive guidance	28	0	1	1	0	30
Experimental session 2: Partitipative-suggestive guidance	7	1	0	0	0	8

disadvantage is the possible introduction of order effects due to having a knowledge of the problem from one trial to the next. The second experimental session was a sample of 16 using the same procedure except for segmenting the sample population into two groups of eight subjects. Each group considered only one of the two guidances.

The subjects were to solve a decision problem that required selection of an appropriate forecasting model for a provided scenario. The forecasting models for selection included those in Figs. 1 and 2. The criteria used for selecting a forecasting model were suggested by [25]. The scenario is in Appendix A. Subjects selected one of four decision strategies, described in Appendix B, to arrive at a solution. The computer-based participative-suggestive guidance was developed in Lotus-1-2-3 with the resulting interface being those of Figs. 1 and 2.

Subjects ‘self-recorded’ their answers using paper and pencils. They were asked to select a forecasting model based upon the information given in the scenario. They were also asked to use the four strategies introduced. The ‘other’ category is combinations of the four different strategies (e.g. use both ‘comparing by pairs’ and ‘satisficing’ strategies).

At the start of the study, a 15-min training session was conducted to provide subjects with an understanding of each supported selection strategy. Subjects were asked to use each of the strategies in a learning exercise to select an apartment. Any question about how to apply the decision strategy on the exercise problem was answered by the facilitator. This ensured the subjects understood the nature of the experimental task and the decision strategies.

In the first experimental session, and for one half of the subjects in the second experimental session, all subjects were asked to use the information provided in Fig. 1 to select a forecasting model. They were allowed use of only paper and pencil for this first task. Subjects recorded their decisions, the confidence they had in their decision (from a low confidence of 1 to high confidence of 100), and the decision strategy they adopted for making their decisions. A total of 20 min was allowed to complete this task.

Following completion of the task, each subject in the first experimental session was asked to repeat the process with the only change being the provision of spaces for using the multi-attribute weighting method on the computer as shown in Fig. 2. Likewise, the remaining half of the subjects in the second experimental session used this version of the spreadsheet. This change in software represents a shift to participative-suggestive guidance [13]. Again, subjects recorded their decisions, the confidence in their decision, and their decision strategy. In the first experimental session, after completion of the task, two other measures—perceived ease of use and perceived usefulness—were elicited using the scales of [26]. These scales range from one to seven with seven being the favorable end.

3. Results

With predefined information, only ten subjects used the multi-attribute weighting method as their decision strategy, as shown in Table 1. However, with the multi-attribute weighting method having a participative-suggestive guidance interface, 35 subjects chose that particular method for their decision strategy. Fig. 3 shows the change in selection

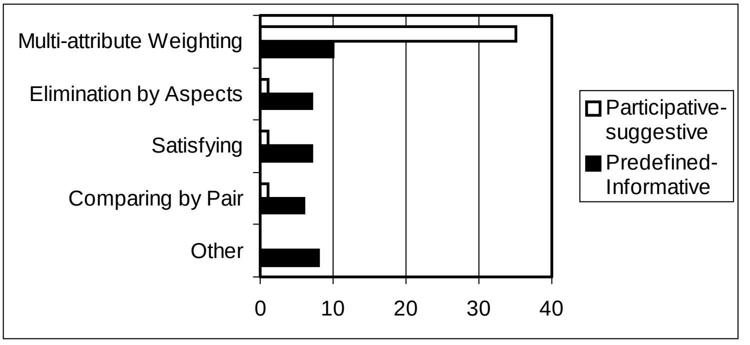

Fig. 3. Differences in method selected by guidance format.

strategies with a corresponding change in guidance. This is a significant change in proportion according to Fisher's Exact Test. In fact, each method showed a significant change in proportions indicating that the software did influence the selection of the model as we expected. Also, by categorizing the results into the Multi-attribute Weighting method and all others, Fisher's Exact Test shows no difference in proportion between experimental sessions for either guidance method, indicating no order effects were significant in the first experimental session.

Table 2 shows the decision changes among the 28 subjects in the first experimental session who used the multi-attribute weighting method. Among the eight subjects who first used the method, only one subject changed his/her decision and the other seven subjects stayed with the same decision. However, nine of twenty subjects who did not adopt the multi-attribute weighting method as their first decision strategy reached different decisions after using the revised format. Eleven subjects did not. The table indicates how many subjects actually arrived at different solutions because of the change in solution procedures encouraged by participative-suggestive guidance.

Researchers have shown a strong relationship between ease of use and usefulness and a user's acceptance of a system [26]. Table 3 shows that twenty-seven out of the thirty subjects in the first experimental session perceived the guided decision aid as easy to use and twenty-four out of thirty subjects perceived the revised aid as useful for their decision making task. The non-parametric Sign Test was conducted on each of these measures [27]. The neutral response of four on the scales is used as the effective zero. Both ease of use and usefulness were in the favorable range at a significance level of 0.05, from which we conclude that subjects perceived the system positively.

Table 2
Decision changes by decision strategy

	Multi-attribute weighting	Other methods
No decision change	7	11
Decision change	1	9
Total	8	20

Table 3
System acceptance metrics

	Ease of use	Usefulness
$<$ 5[a] rating	3 subjects	6 subjects
$>$ = 5 rating	27 subjects	24 subjects

[a] The scale ranged from 1 to 7 with 7 being most favorable.

4. Discussion

This experiment highlights the point that the decisional aid of a DSS can significantly influence users' selection of a decision strategy as well as the decision outcomes. It is not our intent to argue which decision strategies should be implemented for the problem in the experiment, however, DSS interface designers need to take the amount and type of guidance into account.

The type of guidance can impact the model selected during the model selection phase of decision support. This may be a two-edged sword. Indirectly influencing the model selected by a decision maker may direct the user into the selection of a technique that would not otherwise be chosen. If the intent of the DSS is to allow full flexibility and control on the part of the user, then the resulting impact does not match the intent. However, such guidance can also be of assistance to novice users unfamiliar with the problem domain. In this latter case, it may even be desirable to influence the selection of a particular model while still allowing experienced users to apply their own knowledge.

An advantage of this type of guidance is that it can be effective, but also subtle, leaving the users the perception of control. This, along with the positive perception of ease of use and usefulness can lead to a more effective use of the system [11,12]. A disadvantage is that the user's preferred selection strategy may be overlooked. Since different selections of decision models do indeed result in different solutions [28], the DSS may inadvertently lead to a less preferred solution.

To generalize, the guidance portion of the interface design cannot be taken lightly. DSS designers traditionally have many concerns with the impact that their design may have on influencing outcomes. Ease of use and usefulness are appropriate goals, but not at the expense of poor solutions. Thus, structure of the guidance must be added to the list of design concerns that can bias results. The list already includes use of graphics [2], icons [29], menus [1], feedback [30] and other dialogue issues as well as the many issues in model inclusion and data availability [7,31].

The study results must be viewed with caution with respect to generalizations. The only thing shown conclusively is that a variation in decisional guidance can lead to very different results in a decision setting. The formal results cannot be extended to multiple problem domains as each domain may be unique. These limitations do not lighten the caution a DSS designer must place on guidance unless s/he has explored the implications of an intended interface.

Further exploration of guidance may help to clarify existing side effects and allow

for clearer design guidelines. Can participative-suggestive or predefined-informative guidance make a DSS more effective at supporting, not influencing, decision makers? Can suggestive guidance effects be limited to the target of guidance (structuring vs. executing the decision-making process)? Does decisional guidance affect how much time the decision maker spends using a system? Does increased ease of use translate into increased frequency of use? When do the costs of learning the guidance mechanisms exceed the benefits of using them? These and other questions are those researchers must address to assist in the development of future Decision Support Systems.

Appendix A. Decision scenario

Imagine that you are a computer sales manager and are asked by top management to use a structured technique to forecast monthly sales in the future.

- The project is to be done in three months.
- You and your staff are comfortable with mathematical models.
- Historical data on computer sales have been collected industry wide, however, only the last two years of monthly sales data are available.
- There is US$100 000 available for this project.
- A fairly detailed monthly sales forecast report is required.
- The forecasting model will need to be updated every six months.

A decision support system has been proposed by a marketing analyst to support the corporation's forecasting needs. Four forecasting models are suggested by the analyst. A forecasting model may lead to a satisfactory prediction or an unsatisfactory prediction because of a mismatch between the characteristics of the model and the business situation and needs. Your job for now is to select the most appropriate forecasting model for your business needs.

Appendix B. Decision strategies

Multi-attribute weighting:	This technique requires that you consider all the criteria, assign them weights (in terms of their importance or value), and then combine the weighted scores to choose a single model.
Elimination of aspects:	When using this approach, you eliminate the models that do not meet one or more of your criteria. For example, if you do not have the resources to construct a model that is rated 6 or 7 in expense, then you eliminate those models. You evaluate models against each of your important criteria, one at a time. Then you choose the model that is left.

Satisficing:	You seek the model that meets a minimum value for most of your criteria. You apply this judgment to each criterion. You select the model to which most (or all) apply.
Comparing by pair:	When using this technique, you compare two models at a time. You eliminate the least attractive model. Repeat this process until there is only one model left.

Appendix C. Test of forecasting model knowledge

1. Which of the following forecasting models can be developed most quickly?

   Moving average
   Exponential smoothing
   Times series extrapolation
   Box-Jenkins

2. Which of the following forecasting models can be developed least costly?

   Moving average
   Exponential smoothing
   Times series extrapolation
   Box-Jenkins

3. Which of the following forecasting models requires the minimal quantitative capabilities?

   Moving average
   Exponential smoothing
   Times series extrapolation
   Box-Jenkins

4. Which of the following forecasting models can most accurately forecast the future under significant environmental change??

   Moving average
   Exponential smoothing
   Times series extrapolation
   Box-Jenkins

5. Which of the following forecasting models can produce the most detailed results?

   Moving average
   Exponential smoothing
   Times series extrapolation
   Box-Jenkins

6. Which of the following forecasting models can be systematically updated most easily?

Moving average
Exponential smoothing
Times series extrapolation
Box-Jenkins

Please rate your knowledge about forecasting models from 1 (know extremely little) to 7 (very knowledgeable).

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